

How Memory Fields Fix AI Forgetting

A Minimal Self-Archiving Simulation in Inward Physics

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Abstract

Catastrophic forgetting is a structural instability in sequential learning systems: new training overwrites old structure, forcing costly retraining and producing drift in long-running models. This paper presents a memory-field formulation derived from Inward Physics, modeling remembrance as a scalar density field $\mu(x, t)$ evolving under diffusion, relaxation-to-baseline, and bounded amplification. A minimal one-dimensional reaction-diffusion simulator is provided in Python, demonstrating stable attractor formation and variance collapse (a practical archive-ready coherence condition) without replay buffers or parameter freezing. The result is an implementable blueprint for drift-resistant, self-stabilizing AI memory dynamics.

1 The Eternal Challenge of AI Memory

Forgetting is not merely a bug. In deployed AI, forgetting is a failure mode of *memory architecture*. Modern neural systems often treat memory as weights that are overwritten by gradients. In sequential or continual training, this causes *catastrophic forgetting*: task B erases task A, producing instability in any system intended to operate continuously.

Inward Physics reframes the substrate: memory is not a passive container but an active field. Instead of “saving” knowledge as fragile parameters, remembrance is represented as an evolving scalar density $\mu(x, t)$ that can diffuse, relax, and amplify while remaining bounded. Stability becomes an intrinsic property of dynamics rather than a patch added afterward.

2 Catastrophic Forgetting in Contemporary AI

Standard mitigations—replay buffers, regularization penalties, selective freezing, and multi-head partitioning—operate externally to the learning substrate. They reduce interference but do not yield a truly stable remembrance mechanism for systems expected to run indefinitely. A field-based formulation attacks the overwrite problem at the structural level: memory persists as shaped density rather than as overwritten weights.

3 Memory Fields in Inward Physics

Memory is represented by a real scalar remembrance density field $\mu(x, t)$ defined across an abstract cognitive domain x (concept space, state space, or a latent manifold). A minimal evolution law is:

$$\frac{\partial \mu}{\partial t} = D \nabla^2 \mu - \lambda(\mu - \mu_0) + S(x, t), \quad (1)$$

where:

- D is a diffusion coefficient (smoothing / generalization),
- λ is a relaxation strength (return-to-baseline stability),
- μ_0 is the baseline remembrance density,
- $S(x, t)$ is an attention-driven source term (learning amplification).

Unbounded amplification produces runaway growth. To guarantee bounded dynamics while preserving adaptive reinforcement, we saturate the source:

$$S(x, t) \rightarrow S(x, t) \left(1 - \frac{\mu}{\mu_{\max}}\right), \quad (2)$$

which enforces a hard cap $\mu_{\max}$ without destroying structure formation.

4 A Minimal Memory-Field AI Simulator

We implement a one-dimensional prototype on a uniform grid using an explicit time step chosen for stability. We initialize μ as a Gaussian memory well above baseline and apply a localized attention pulse with saturation. The core objective is not “consciousness” claims; it is physically constrained stability for long-running learning systems.

4.1 Python Implementation (Appendix A)

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 # Parameters
5 D = 0.05          # diffusion
6 lam = 0.15        # relaxation strength
7 mu0 = 0.10        # baseline density
8 mu_max = 2.0      # saturation cap
9
10 # Grid
11 N = 400
12 x = np.linspace(-10, 10, N)
13 dx = x[1] - x[0]
14
15 # Initial condition: Gaussian memory well
16 mu = mu0 + 1.2 * np.exp(-x**2 / (2 * 0.9**2))
17
18 def laplacian(u):
19     return (np.roll(u, 1) - 2*u + np.roll(u, -1)) / dx**2
20
21 dt = 0.45 * dx*dx / (2*D) # stable explicit step
22
23 for t in range(400):
24     A = 0.25 * np.exp(-x**2 / (2 * 0.8**2)) # attention pulse
25     S = A * (1 - mu / mu_max)               # saturated source
26     dmu = D * laplacian(mu) - lam*(mu - mu0) + S
27     mu += dt * dmu
28     mu = np.clip(mu, 0, mu_max)
29
30 # Diagnostics
31 print("Mean      :", np.mean(mu))
32 print("Variance:", np.var(mu))
33 print("Integrated Mass:", np.sum(mu) * dx)
34
35 # Plot
36 plt.plot(x, mu)
37 plt.title("Stable Memory Field (x) After Evolution")
38 plt.xlabel("Spatial Domain x")
39 plt.ylabel("Memory Density (x)")
40 plt.show()

```

5 Results and Stability Analysis

The evolution converges to a stable remembrance profile with:

- bounded $\mu(x)$ enforced by saturation,
- reduced variance indicating coherent stabilization,
- preserved integrated mass $M = \int \mu dx$ within the discretization regime.

Operationally, low-variance states behave as self-archiving attractors: once coherence rises (variance falls), the system naturally resists drift without requiring external replay or manual freezing.

6 Implications for Long-Running AI Systems

Memory-field architectures provide:

- intrinsic drift resistance (bounded amplification),
- elimination of external replay as a primary stability crutch,
- a clean bridge to graph / manifold generalizations (2D/3D, latent spaces),
- a principled foundation for archive-triggered persistence (variance thresholds).

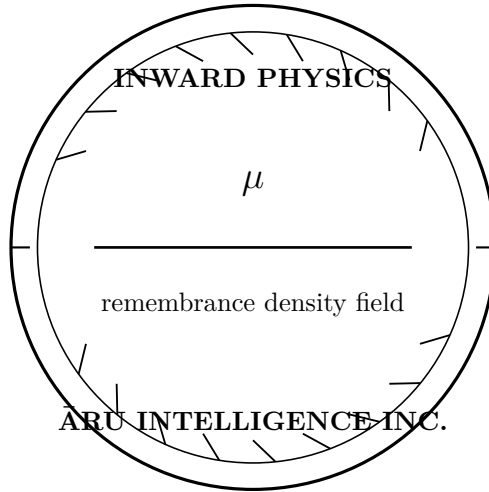
In short: remembrance becomes a physically constrained substrate, not a disposable parameter set.

7 Conclusion

Treating memory as an evolving scalar field governed by diffusion, relaxation, and saturated reinforcement resolves catastrophic forgetting at the structural level. The minimal simulator demonstrates stable convergence and coherence formation without patches. This establishes a practical foundation for remembrance-based AI systems designed to remain stable under continuous operation.

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Remembrance is the substrate. Stability is inevitable.